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HEALTH MANAGEMENT ASSOCIATES

EVALUATING THE EFFECTS OF HOSPITAL CONSOLIDATION:
HOW SENSITIVE IS THE DISCRETE CHOICE ECONOMETRIC MODEL IN IDENTIFYING
HOSPITAL COMPETITORS?

PRESENTED TO
CALIFORNIA HEALTHCARE FOUNDATION

BY
LISA MAIURO, PHD, AND PAUL NIEMANN, PHD

AUGUST 2015

*Research and Consulting in the Fields of Health and Human Services Policy, Health Economics
and Finance, Program Evaluation, Data Analysis, and Health System Restructuring*

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INTRODUCTION AND SUMMARY

In 2013, at the request of the California Department of Justice (DOJ), Health Management Associates (HMA) examined the likely competitive effects of the proposed affiliation of Children’s Hospital and Research Center of Oakland (Oakland Children’s) and University of California, San Francisco (UCSF). Using a relatively new approach to competitive effects analysis herein referred to as the “selection model,” HMA was able to quantify the direct competition between the two hospitals. This measure indicated the extent to which the hospitals were substitutes for each other and therefore whether significant market power would be created if the two organizations were allowed to negotiate as a single entity. While this approach has significant advantages over other approaches—for example, the Elzinga-Hogarty (E-H) and critical loss analyses that have been widely applied in the past—it was clear from our work that this alternate approach was not a purely “plug-and-chug” model, and there were some questions regarding the robustness of the results to variations in variable definitions and model specifications. For the purposes of both understanding the selection model better and increasing the efficiency with which we applied the selection model to healthcare transactions in the future, we chose to examine these questions in the context of three previous hospital mergers reviewed by either the DOJ or Federal Trade Commission (FTC), two entities charged with enforcing antitrust law. (Please see the companion California HealthCare Foundation paper, *Balancing Act: Consolidation and Antitrust Issues in Health Care*, for more information on antitrust laws and issues facing California providers and consumers.)

This paper briefly reviews the recent history of hospital antitrust methods used to define markets, describes the selection model currently endorsed by the FTC for antitrust analysis, and then explores the sensitivity of this new approach to model variations. We apply the selection model to three hospital transactions in California that were reviewed under older methods and evaluate whether the findings from the new approach using the selection model would have supported those consolidations from previous approaches as well as the extent to which the model’s results are sensitive to changes in the model specifications.¹

The results of this work demonstrate that the model was relatively robust to variations in model specifications with perhaps the exception of public payers. Inclusion or exclusion of patients covered by Medicare and Medicaid had the largest impact on the diversion ratios. We did not find that the results of the modeling alone would have changed the decision of the antitrust enforcement agencies to approve or deny the three hospital transactions we considered as case studies. Given that there is no bright-line test for the diversion ratio, it is important to consider the ratio in conjunction with other factors incorporated in an antitrust review as outlined in the 2010 Merger Guidelines.

¹ Please note, for simplicity, we sometimes refer to healthcare transactions including mergers, consolidations and affiliations, for purposes of discussion, interchangeably, however, each has its own technical definition.

One of the advantages of the model is that it does not presume a specific geographic market as in older approaches and is robust to the inclusion of hospitals that may not have much actual competitive relevance. However, for California, with 3.0 million discharges from 372 hospitals, computational limits impose restrictions on the number of hospitals that can feasibly be included in the choice set since the model examines each patient hospital combination.^{2,3,4}

USING THE CONDITIONAL CHOICE MODEL FOR HOSPITAL ANTITRUST ANALYSIS

The Conditional Choice Model: Background

In 2010, reflecting substantial economic learning and agency practice, the FTC-DOJ revised the Horizontal Merger Guidelines for the first time since 1992. The 2010 Guidelines updated the treatment of unilateral price effects to reflect the substantial change in economic learning and agency practice since 1992. Two aspects of that updating are of special significance: (1) reduced emphasis on market shares and (2) introduction of the “value of diverted sales,” or in the case of hospitals, diverted patients, as an indicator of upward pricing pressure.⁵ Subsequently, the diversion ratio has been used more frequently as one component for assessing competitive effects of hospital mergers. The diversion ratio quantifies the extent of direct competition between a product sold by one merging firm and a product sold by the other merging firm. It reflects the fraction of unit sales lost by the first product due to an increase in its price that would be diverted to the second product with higher diversion ratios, indicating a greater likelihood of unilateral price effects.

In early October 2012, during an American Bar Association program on antitrust and healthcare issues, FTC Deputy Director for Health Care and Antitrust Leemore Dafny said that the FTC will focus on how patients purportedly react to price increases, as measured by “diversion ratios,” rather than geographic market share as commonly calculated using the Herfindahl-Hirschman Index (HHI), when deciding which hospital mergers to investigate further for potential anticompetitive effects. Dafny stated that the FTC will focus on diversion ratios rather than geographic markets because relying on geographic market overlaps in hospital mergers may be inadequate for identifying the true

² We did not incorporate the outside option that includes hospitals which are typically on the periphery of the area being considered as well as hospitals that have very little competitive relevance.

³ *Hospital Annual Financial Data*, OSHPD, 2013, <http://www.oshpd.ca.gov/HID/Products/Hospitals/AnnFinanData/PivotProfles/default.asp>.

⁴ A model of patient choice of hospitals can be estimated with up to 50 or so hospitals without much computational burden. Subramaniam Ramanarayanan, *Diversion Analysis as Applied to Hospital Mergers: A Primer*, NERA Economic Consulting Group, June 24, 2014, http://www.nera.com/content/dam/nera/publications/archive2/PUB_Diversion_Analysis_Hospital_Mergers_0614.pdf.

⁵ Carl Shapiro, “The 2010 Horizontal Merger Guidelines: From Hedgehog to Fox in Forty Years,” *Antitrust Law Journal* 77, no. 1 (2010).

source of potential competition problems. The inability to convincingly define geographic markets for hospital care has been cited as the primary determining factor in six of the government's eight unsuccessful merger challenges between 1994 and 2005.⁶ A large part of the problem is that earlier approaches to market definition did not reflect the patient's willingness and ability to find a substitute hospital *outside* the hospitals involved in the proposed merger. Subsequently, the FTC's emphasis is currently on whether patients would be willing and able to substitute one hospital for the other if one hospital decided to raise prices for services, using the proportion of patients who would switch between them in response to a change in prices, or the diversion ratio. A key feature of the diversion ratio is that it does not rely on any one particular geographic market definition to provide information on how a hospital merger might affect competition. The new Guidelines promote the diversion ratio as an important tool for evaluating competitive effects; however, it is important to remember that it is taken into consideration with the strength of other evidence and is influential but not dispositive in isolation.⁷

The Conditional Choice Model: General Approach

The purpose of a discrete choice conditional logic specification is to capture the relationship between the actual hospital choices made by patients and the characteristics of patients and hospitals in the sample that drive these choices. The general approach uses patient discharge data, combined with data on hospital characteristics, to estimate the probability that a patient with a given set of socioeconomic and clinical characteristics will choose a given hospital in the sample. By summing these estimated probabilities we generate the expected number of patients that will choose each hospital included in our dataset. Using the Conditional Choice model we can then estimate which hospital(s) patients would choose in the event that one of the hospitals involved in a merger were to become unavailable to the patient. For instance, if, because of a merger agreement, the acquired hospital were no longer available to patients due to exclusion from an insurance plan's network because of price increases, the model provides an estimate of where those patients would most likely go. The diversion ratio is an estimate of the fraction of patients that would go to a specific hospital as a result of one of the hospitals, involved in the transaction, becoming unavailable. This is important, as it provides a measure of competitiveness in the marketplace. Specifically, it provides a picture of which hospitals are the closest competitors of the hospitals involved in the merger. In the event that a large number of the acquired hospital's patients would choose to go to the merging hospital, the result would suggest that the acquiring hospital may be the closest substitute, and there may be antitrust issues that should be examined in greater depth.

Hypothetically, suppose that during the year, 250 patients selected Hospital A. Now suppose that Hospital A is no longer available to these patients. Of these 250 patients,

⁶ Martin Gaynor, Samuel Kleiner, and William Vogt, *A Structural Approach to Market Definition with an Application to the Hospital Industry*, March 14, 2012, http://www.andrew.cmu.edu/user/mgaynor/Assets/MktDefPaper_Revision_Final.pdf.

⁷ *Roundtable on Market Definition*, FTC, June 7, 2012, https://www.ftc.gov/sites/default/files/attachments/us-submissions-oecd-and-other-international-competition-fora/062012Market%20definition_U.S.pdf.

suppose that 40 would select Hospital B. Then the diversion ratio would be $40 / 250 = 0.16$. If all of the 250 displaced patients went to Hospital B, then the diversion ratio would be 1, indicating that a merger of hospitals A and B would involve a loss of competition because Hospital B is the only substitute for Hospital A. On the other hand, if the diversion ratio were 0—that is, none of the 250 patients went to Hospital B—the merger would involve no loss of competition since Hospital B is not a substitute for, nor a competitor of, Hospital A. The magnitude of the diversion ratio provides a quantitative indication of the alternatives available to patients as a result of a proposed merger. Understanding this provides suggestive evidence regarding market power and possible price increases as a result of the merger. This approach has considerable advantage over market share or HHI estimates in that it estimates how “close” two products are, a concept that is not captured by market share figures.

Diversion ratios are suitable for revealing which products, in this case hospitals, are close substitutes. A diversion ratio close to 1 between Hospital A and Hospital B suggests that Hospital B would likely be the sole substitute, and significant market power would be exercised if the two organizations were allowed to merge. Perhaps with the exception of diversion ratios close to 1, however, there is no clear “bright-line” threshold for a diversion ratio to indicate unilateral pricing effects.

The Gross Upward Pricing Pressure Index and the Upward Pricing Pressure Index

Diversion ratios are useful insofar as we can use them to consider the extent to which the proposed merger might lead to a loss of competition. A high diversion ratio between hospitals is an indication that the hospitals are close substitutes, but it is helpful to have a measure of what this implies for post-merger pricing. One such measure, incorporating the diversion ratios from the Conditional Choice model, is the Gross Upward Pricing Pressure Index (GUPPI), a relatively new tool to assess unilateral merger price effects in markets for differentiated products that has become prominent since the release of the 2010 Horizontal Merger Guidelines.⁸

The GUPPI calculation does not rely on market definition or concentration. It measures the value of sales diverted to one merging firm’s product due to a post-merger price increase of the other merging firm’s product, relative to revenue lost due to fewer sales of the product with the price increase. The GUPPI is similar to another post-merger pricing measure, the Upward Pricing Index (UPPI), but does not take any transaction efficiencies into account. The UPPI theory provides a measure of the combined firm’s incentives to increase price post-merger and uses three key inputs: the diversion ratios, the pre-merger gross margins, and an estimate of or assumption about the likely efficiencies stemming from the merger.⁹ However, while merger-specific efficiencies are taken into

⁸ The FTC does not generally consider the GUPPI or UPPI in hospital competitive effects analyses.

⁹ Subramaniam Ramanarayanan, *Diversion Analysis as Applied to Hospital Mergers: A Primer*, NERA Economic Consulting Group, June 24, 2014, http://www.nera.com/content/dam/nera/publications/archive2/PUB_Diversion_Analysis_Hospital_Mergers_0614.pdf.

account in a competitive effects analysis, quantifying efficiencies resulting directly from a transaction is often tricky and subjective.¹⁰ Thus, the GUPPI is a simpler measure, since it doesn't take into account the uncertainty associated with quantifying prospective efficiencies.

Formally, the GUPPI for the merger of Hospital A with acquiring Hospital B is calculated using the following formula:

$$GUPPI = DR \times m_2 \times P_2 / P_1$$

where *DR* is the diversion ratio from Hospital A to Hospital B, *m*₂ is the variable pre-merger profit margin of Hospital B as a fraction of pre-merger revenue, and *P*₂ / *P*₁ is the relative per merger price of Hospital B (relative to Hospital A). For example, if *DR* = 20%, *m*₂ = 50%, and *P*₁ = *P*₂, then *GUPPI* = 10%.

Thus, the GUPPI is higher when either the diversion ratio to the merging partner's product is higher, or the profit margin of the merging partner's product is higher, or the relative price of the merging partner's product is higher (or all three).¹¹ The GUPPI is useful in that, while there is no "bright-line test" for either diversion ratios or the GUPPI, the products of the merging firms are likely to compose a relevant antitrust market or at least give rise to antitrust concerns if the GUPPI is at least twice the level of "small but significant non-transitory increase in price" or "SSNIP" (usually regarded as a 5% price increase sustained for at least one year) used for market definition.

However, the 2010 Merger Guidelines and the current approach to antitrust analysis suggests that the GUPPI, like the diversion ratio, should be used in conjunction with other factors reviewed in merger analyses, and are not in isolation dispositive of competitive effects.

It should be noted that the GUPPI and the UPPI are not used to a significant degree in the analysis of hospital mergers by enforcement agencies. This is due to the unique characteristics of the hospital markets. In our analysis we have elected to use the UPPI to provide general guidance on the interpretation of the diversion ratios.

¹⁰ Examples of efficiencies may include cost reduction from service-line consolidations, elimination of redundancies (staff, equipment), capital expenditure avoidance, and purchasing economies.

¹¹ Serge Moresi, "The Use of Upward Price Pressure Indices in Merger Analysis," *The Antitrust Source*, February 2010, http://www.americanbar.org/content/dam/aba/publishing/antitrust_source/Feb10_Moresi2_25.f.authcheckdam.pdf.

TESTING THE SENSITIVITY OF THE CONDITIONAL CHOICE MODEL

Defining the Base Model

Our base model, serving as a springboard for the model sensitivity analysis as applied to three case study mergers, is consistent with Capps et al.¹² We chose to conduct a sensitivity analysis with three goals in mind: (1) determine which input parameters contribute the most to output variability, (2) determine which parameters can be eliminated from the model and maintain the reliability and accuracy of the model, and (3) identify options for reducing the system resources necessary to running the model. We prepared the data and ran the analyses using Stata. Our model was relatively resource intensive, taking an average of 7 hours to run the data preparation programs and approximately 18 hours to run all the analyses for each merger we investigated. As a result, the analysis of a given merger took approximately 25 machine hours to run from start to finish. This time for runs, of course, depends in part on the computing resources available, a topic we discuss in more detail later in this brief. California poses greater challenges simply due to its size and the number of hospitals in the state—366 hospitals, of which 305 were general acute care in 2013.¹³ With more than 3 million acute care discharges, excluding duplicate claims for newborns, a full dataset including the various combinations of each patient with each hospital would approach 1 billion rows of data. Consequently, one of our goals was to identify logical ways to either reduce the number of observations or exclude fields that did not materially affect the model results.

Below we describe the data sources and model specifications for the base model that was applied to all three merger case studies.

Data Sources

Data for the model were obtained from multiple sources including:

- Office of Statewide Health Planning and Development (OSHPD) Patient Discharge Data (PDD): 1998 PDD data were used for Summit/Sutter, 2009 for Victor Valley Community Hospital / Prime, and 2011 for St. Joseph / Hoag. These data contain inpatient information on all patients discharged from California hospitals including diagnosis, age, and payer, as well as a variety of clinical and demographic data.
- OSHPD Hospital Annual Financial Disclosure Data: Data for the hospital's fiscal year prior to the merger were used. These data include descriptive and financial information on hospitals, and selected fields were used as independent variables as described in greater detail below.
- OSHPD Annual Utilization Report of Hospitals: Data for the hospital's calendar year were extracted from the year prior to the merger where available. These da-

¹² Cory Capps, David Dranove, and Mark Satterthwaite, "Competition and Market Power in Option Demand Markets," *RAND Journal of Economics* 34, no. 4 (2003): 737.

¹³ *Hospital Annual Financial Data*, OSHPD, 2013. Based on hospitals' fiscal year.

ta include summary utilization information on hospitals, and selected fields were used as independent variables as described in greater detail below. Where possible, we relied on this file for hospital data since the facility information is provided with less aggregation.¹⁴

- US Census Bureau, 2007-2011 American Community Survey: Data on income by race by ZIP Code Tabulation Areas (ZCTA) were used in the model as independent variables. ACS data on income by race were not available for the year prior to the approval of the Summit/Sutter merger, so we used US Census Data. Since OSHPD patient-level data include the patient's zip code, and census data was available by ZCTA, it was necessary to map the ZCTAs to zip codes.
- Travel times from 2010 MapPoint: We used MPMileage, which uses MapPoint to batch process drive times. The version of MapPoint we used is from 2010. MPMileage obtains estimated travel time by plugging two zip codes into MapPoint and identifying the quickest route. The process is similar to what people can do on Google Maps to get driving directions. MPMileage allows use of an Excel file with many zip code pairings to quickly calculate routes and travel times.
- National Cancer Institute (NCI): The NCI website (<http://www.cancer.gov/researchandfunding/extramural/cancercenters/find-a-cancer-center>) is used to identify California hospitals that focus on cancer care.
- American Hospital Association (AHA): The AHA website (<http://www.heart.org>) is used to identify hospitals that focus on cardiac care. We include California hospitals that have an Advanced Certification in Heart Failure and hospitals that have STEMI (heart attack) Receiving Center Accreditation— that is, those hospitals that participate in coordinated systems of care for ST-elevation myocardial infarction (STEMI) and meet certain standards.
- Becker's Hospital Review of hospitals with great orthopedic programs. (<http://www.beckershospitalreview.com/lists/101-hospitals-with-great-orthopedic-programs.html>, accessed 6/15/2015) This review provides a list of hospitals that specialize in orthopedic care in 2012.

Model Hospitals and Variables

Our base model analysis begins with PDD for the year prior to the merger for each of the three case studies. We retained all general acute care California zip code discharges. We identified the zip code for the patient's residence for all acute care patients from the facilities involved in the transaction. For the Hoag merger, we kept all zip codes that composed the largest patient pools up to approximately 80% of the total discharges from the facilities depending on the merger (Table 1).¹⁵ Ideally, we would have included 100% of

¹⁴ Some hospitals may have multiple physical facilities that report under a consolidated license number in OSHPD's Hospital Annual Financial Disclosure reports; however, they are required to report data for OSHPD's Annual Utilization reports at an individual level.

¹⁵ Some zip codes were excluded if very small numbers of patients were drawn to the focal hospitals. This method is consistent with Gai 2007, in which the data included at least 92% of all patients

total discharges given that a key feature of the model is that it does not rely on any one particular geographic market definition to provide information on how a hospital merger might affect competition. However, this would create a dataset for analysis with more than 970 million observations, which was beyond our computing capacity. (Please see discussion below on the issues regarding computer resources required for the model.) As the number of hospitals in the acquiring system becomes larger, the analysis dataset becomes larger because all the system hospitals are treated as part of the merger. Depending on the number of hospitals, the dataset can eventually become too large for available system resources. The Victor Valley/Prime and Summit/Sutter transactions both involved a hospital associated with a hospital system that included several hospitals. (See Appendix A.) For this reason, the cutoff used was 75% for Victor Valley / Prime and 65% for Summit/Sutter. It is important to note that in this step we are not eliminating patients outside the 75% and 65% criteria but simply hospitals. So, for example, the transaction involving Victor Valley Hospital in Victorville, California, located in San Bernardino County with the Prime hospital system identifies the hospital discharges for Victor Valley and all the Prime hospitals listed in Appendix A. These include hospitals located as far away as Inglewood in LA County and Anaheim in Orange County; both cities are approximately 100 miles from Victorville and in urban areas with many other hospitals.

After identifying all hospitals that discharged acute care patients that lived in the set of retained zip codes, we examined the acute care discharges in captured zip codes for each hospital. If the total number of acute care discharges for a given hospital did not compose at least 10% to 20% of the total discharges for that hospital, depending on the specific case study, then that hospital was deemed to be too small of a player in the relevant market and was removed from the analysis (Table 1). The following table summarizes the data selection criteria for each of the three case study transactions and the resulting number of hospitals and raw discharges.

Table 1. Hospital Selection Criteria for Each Case Study

Case Study Merger	Zip Code Selection	Final Hospital Selection	Raw Number of Hospitals	Raw Number of Discharges
St. Joseph / Hoag	80%	10%	42	3,058,921
Victor Valley / Prime	75%	15%	56	3,097,609
Summit/Sutter	65%	20%	70	3,441,469

Our independent or explanatory variables are organized into four categories:¹⁶

- A. Hospitals Characteristics
- B. Hospital Services
- C. Patient Demographic Data

treated in areas served by the merging hospitals, although our thresholds needed to be smaller in order to construct a dataset that could be analyzed with current resources due to the large number of patient discharges. Yunwei Gai, "An Evaluation of Willingness-To-Pay Methods for Pre-Merger Investigation and Certificate of Need Licensing in Local Hospital Markets" (PhD dissertation, Florida State University, 2007),

<http://diginole.lib.fsu.edu/cgi/viewcontent.cgi?article=1520&context=etd>.

¹⁶ Per Cory Capps, David Dranove, and Mark Satterthwaite, "Competition and Market Power in Option Demand Markets," *RAND Journal of Economics* 34, no. 4 (2003): 737.

D. Patient Health and Travel Characteristics

These four groups map to the four matrices described below under the section titled Model Specification.

A. The hospital characteristics used in the analysis include:

1. For-Profit: This is a dichotomous variable that takes a value of 1 to indicate a for-profit hospital. (Note: Nonprofit is the omitted variable.)
2. Teaching Status (Teach): This is a dichotomous variable that takes a value of 1 to indicate a teaching hospital (this is a proxy measure of a tertiary care hospital).
3. RNs per Bed: This is a measure of nursing intensity, care intensity, and some reputational effects. It is calculated by dividing the Total Paid Hours for all RNs by 2,080. (One full-time equivalent [FTE] equals 2,080 hours per year.) Adjusted Occupied Beds equals (Occupancy Rate times Number of Beds) times (Total Gross Patient Revenue divided by Gross Inpatient Revenue).
4. Capital Intensity: This is a measure of the capital intensity as measured by the hospital's reported net property plant and equipment per adjusted patient day.
5. Licensed Hospital Beds: This variable indicates the number of licensed beds in the hospital.
6. Transplant: This variable indicates whether the hospital had performed any transplants the year prior to the merger. It is a measure of the relative technological sophistication of the hospital.

B. Hospital services

The model includes information on individual areas of hospital service specialization. However, there is no consensus on how "specialization" is defined, and the topic of methodologies for characterizing hospital specialization is beyond the scope of this paper. Briefly, there are several ways one could look at specialization. Some of these approaches include (1) extracting information from hospital websites and marketing materials, (2) identifying hospitals with certifications and accreditations provided by external organizations, and (3) reviewing service data submitted to a state agency—for example, OSHPD. In the case of retrospective case studies, accessing older data based on marketing by the hospital or accreditation or certification by other agencies is sometimes difficult.

Hospital service indicators, as identified by third-party organizations, were used as explanatory variables in the SJHS/Hoag model since these data were published in close approximation to the date of the transaction, and included.¹⁷

¹⁷ The date that the data on specialization were collected from AHA, NCI, and Becker's Review was not readily available. However, we assume that the data are close enough to be reliable indicators for service specialization for 2011.

1. Cardiac Care: Using the most recently available American Heart Association data, we include an indicator for hospitals that have an Advanced Certification in Heart Failure and hospitals that have STEMI (heart attack) Receiving Center Accreditation – that is, those hospitals that participate in coordinated systems of care for STEMI and meet certain standards.
2. Cancer Care: This variable indicated whether the hospital specialized in cancer care as listed on the NCI website.¹⁸
3. Orthopedic Care: This variable indicated whether the hospital specialized in orthopedic care as designated by Becker’s Hospital Review of hospitals with great orthopedic programs in 2012.¹⁹

For 1998 and 2009 we relied on OSHPD hospital data for indicators of specialization and looked at three areas for the hospitals in each of those years: respiratory care, rehabilitation, and cardiovascular care, discussed below in more detail under Testing Assumptions and Model Specifications.

C. The patient characteristics used as explanatory variables in the model included:

1. Female: This is a dichotomous variable indicating if the patient is female. Patients whose gender was listed as Other or Unknown, or whose gender was not listed, were removed from the analysis.
2. Age at Admission: This indicates the patient's age in years at the time of admission.
3. Average Income: This indicates average income by race in the patient's zip code from the 2011 American Community Survey.
4. Race: The patient's race was used only to assign the median income by race in the patient’s zip code using the 2011 American Community Survey results.
5. Payer: This indicates the primary payer for the hospital stay.
 - i. Medicare/Medicaid: Dichotomous variable indicating if the patient is a Medicare or Medicaid client. This was taken from the payment category indicator in the PDD. Patients with a payment category coded as Invalid/Blank, or with no payment category coded, were dropped from the analysis. Note that the omitted variable is all other payment categories except Private Coverage and Self-Pay.
 - ii. Commercial Coverage: Dichotomous variable indicating if the client has private health insurance coverage. This was taken

¹⁸ “Find a Cancer Center,” National Cancer Institute, <http://www.cancer.gov/researchandfunding/extramural/cancercenters/find-a-cancer-center>.

¹⁹ “101 Hospitals with Great Orthopedic Programs,” Becker’s Hospital Review, <http://www.beckershospitalreview.com/lists/101-hospitals-with-great-orthopedic-programs.html>.

from the payment category indicator in the discharge data. Patients with a payment category coded as Invalid/Blank, or with no payment category coded, were dropped from the analysis. Note that the omitted variable is all other payment categories except Medicare/Medicaid and Self-Pay.

- iii. Self-Pay: Dichotomous variable indicating if the client was responsible for paying their own hospital bill. This was taken from the payment category indicator in the discharge data. Patients with a payment category coded as Invalid/Blank, or with no payment category coded, were dropped from the analysis. Note that the omitted variable is all other payment categories except Medicare/Medicaid and Private Coverage.
- iv. Managed Care: This is a dichotomous variable indicating if the coverage is HMO or non-HMO managed care in contrast to fee-for-service for the following categories: Medicare, Medi-Cal, Private Coverage, Workers' Compensation, County Indigent Programs, and Other Government.

D. The patient health and travel indicators used as explanatory variables in the model included:

1. Scheduled: This is a dichotomous variable indicating that the hospital admission was scheduled (arranged with the hospital at least 24 hours prior to the admission).
2. Length of Stay: This indicates the patient's length of stay in days. This is used as a rough measure of acuity.
3. Number of Other Diagnoses: This is the number of other diagnoses included in the patient's discharge record, truncated at 24. This is used as a measure of acuity, consistent with the literature.
4. Number of Other Procedures: This is the number of other procedures, truncated at 24. This is used as another measure of acuity.
5. Neoplasm: This is a dichotomous variable indicating cancer based on a principle diagnosis of 140-239.
6. Circulatory: This is a dichotomous variable indicating a circulatory condition based on a principle diagnosis of 390-459.
7. Respiratory: This is a dichotomous variable indicating a respiratory condition based on a principle diagnosis of 460-519.
8. Birth Defects: This is a dichotomous variable indicating a principle diagnosis in the congenital anomalies diagnosis group (birth defects).
9. Perinatal: This is a dichotomous variable indicating a principle diagnosis in the perinatal disorders diagnosis group.
10. Time to Hospital: This is the estimated time of travel from the centroid of the patient's zip code to the centroid of the zip code in which the hospi-

tal is located. This was obtained using MPMileage as a front end to the 2010 version of MapPoint. This was calculated for every pairwise combination of hospitals and patient zip codes.

Model Specification

The analysis proceeded in two stages. In the first stage, we estimate the probability that each patient will choose one of the remaining hospitals as a function of hospital and individual characteristics, and in the second stage we use those results to calculate the diversion ratio.

Stage 1: Selection Model Estimation

Using the selected hospital and patient characteristics and knowing the hospital that the patient selected, we estimate the quantitative impact that each of the hospital and patient characteristics have on the probability of a patient selecting a hospital. From these results, we can estimate the probability that any given patient will choose any of the hospitals that have been retained in our dataset, consistent with the model first proposed by Capps et al.²⁰

Data are organized into four groups (or matrices): two groups for hospital data and two groups for patient data. The first group of hospital data (matrix R) contains hospital characteristics that are common across all patient conditions—for example, hospital ownership type and size. The second group (matrix S) of hospital data contains information on specific hospital services—for example, does the hospital offer tertiary care.

Patient data are also broken into two groups (or matrices). The first group of patient data (matrix Y) contains patient socioeconomic and demographic characteristics. The second group of patient data (matrix Z) contains patient clinical characteristics, such as select principle diagnosis code groups. Our selection model also uses the approximate travel time from the patient's residence to each of the hospitals in the dataset.

For this analysis, hospital matrix R, with key hospital characteristics, contained the following variables:

- For-Profit
- Teach
- FTEs per Adjusted Bed
- Capital Intensity
- Hospital Licensed Beds
- Transplant

The hospital matrix S, with key hospital services, contained the following variables, depending on the model and the case study:

- Trauma Care Indicator (intended as a proxy for higher technology level)
- Neonatal Intensive Care Unit
- Cardiac Care
- Orthopedic Care

²⁰ Cory Capps, David Dranove, and Mark Satterthwaite, "Competition and Market Power in Option Demand Markets," *RAND Journal of Economics* 34, no. 4 (2003): 737.

- Cancer Care
- Rehabilitation
- Respiratory Diseases

The patient matrix Y, with patient demographic information, contained the following variables:

- Gender
- Age at Admission
- Income
- Insurance Coverage
 - Medicare/Medicaid
 - Private Coverage
 - Self-Pay
 - Managed Care Coverage

The patient matrix Z, with information on what services patients used, contained the following variables:

- Scheduled Admission vs. Unscheduled Admission
- Length of Stay
- Transplant
- Number of Other Diagnoses
- Number of Other Procedures
- Neoplasm
- Respiratory Condition
- Circulatory Condition
- Birth Defects
- Perinatal
- Time to Hospital

For descriptions of these variables, see the Model Hospitals and Variables section of this report above.

The model hypothesizes that patients will choose the hospital that will provide them with the greatest satisfaction based on the hospital and patient characteristics collected in the datasets. The purpose of running the statistical selection model is to determine the magnitude of the impact of each of the measures, either individually or in combination, to ultimately determine the most likely hospital choice if a specific hospital is no longer an option.

Thus the model that we estimated assumes that patient *i*'s satisfaction with hospital *j* is based on the following specification:²¹

$$U_{ij} = \alpha R_j + H_j \beta X_i + \tau_1 T_{ij} + \tau_2 T_{ij} \cdot X_i + \tau_3 T_{ij} \cdot R_j + \epsilon$$

where U_{ij} is patient *i*'s satisfaction with hospital *j*, R_j is the characteristics of hospital *j* that are common across all patient conditions, H_j and X_i in the second term represent the interaction between all hospital characteristics (matrix *H* comprises matrices *R* and *S* com-

²¹ Ibid.

bined), T_{ij} represents the approximate travel time between patient i 's residence and hospital j . In the fourth term, the travel time interacts with the combined patient data (matrix X comprises matrices Y and X combined). The second-to-last term represents the approximate travel time from patient i 's residence to hospital j interacted with the characteristics of hospital j that are common across all patient conditions. The final term represents the error term, or the elements of the patient's choice of hospital that cannot be captured by this model. The terms a , β , τ_1 , τ_2 , and τ_3 are all parameters to be estimated.

Note that patient demographic characteristics do not enter the equation on their own because those characteristics do not change if a patient chooses one hospital or another. Whether a Hispanic woman chooses to go to Hospital A or Hospital B, she remains a Hispanic woman. The only way that race or gender would enter the selection estimation is if some characteristic of the hospital interacts with race or gender to impact the decision to select that hospital or not.

Using this model of the patient's satisfaction with a given hospital, we can estimate the patient's probability of choosing a given hospital as a function of both the patient and hospital characteristics, using the selection model.²²

Stage 2: Diversion Ratio Estimation

For each case study, once we have estimated the probability that each patient will choose each hospital, we can hypothesize what would happen if one of the hospitals involved in the transaction were no longer a viable option for patients that selected any of the hospitals involved in the transaction. For example, in the St. Joseph Health System (SJHS) and Hoag transaction, we estimate where Hoag Memorial Hospital patients would go if they could not go to Hoag Memorial Hospital. By hypothesizing that a particular hospital is no longer an option, we can estimate where these patients would go, thereby providing a measure of the substitutability of the hospitals involved in the affiliation agreement. We estimate this by eliminating the target hospital and, with our estimation of each patient's probability of choosing any given hospital in our data, determine the expected number of patients in each of the remaining hospitals. The difference between the new patient load and the original estimated patient load is the number of patients that each hospital gains from the eliminated hospital. By dividing by the number of patients that were estimated to have picked the eliminated hospital, we arrive at the diversion ratio. Where there is a multihospital system involved in the transaction—for example, in the case studies involving SJHS and Sutter—the diversion ratios of the system hospitals are summed since presumably they have bargaining leverage as a system. One of the attractive features of the diversion ratio is that, as a ratio, it is not dependent on specific patient caseload estimates.

²² Technically, the conditional selection model estimates the equation
$$s_j = \frac{U_j}{\sum_{j \in G} U_j}$$
 where s_j is the probability a patient chooses hospital j , U_j is the satisfaction the patient receives from hospital j , and G represents the set of all hospitals available to the patient.

Testing Assumptions and Model Specifications

In an effort to better understand what factors have the greatest impact on the diversion ratio, we consider the following model adjustments:

- Hospital readmissions
 - Rationale: In the base model all discharges were treated as independent events, even for the same patient. However, it may be that a positive or negative experience in a previous visit to a hospital would make a patient more or less likely to use the hospital previously visited, and therefore we would want to take into account the effect of unscheduled readmissions at less than 30 days.
 - Base model: Treat all discharges as independent events.
 - Test: Identify any admission for a given patient that was unscheduled and within 30 days of the initial admission. Travel time and admission source or condition.

- Interaction between travel time and condition
 - Rationale: In the base model we consider the travel time from the patient's zip code to any of the hospitals included in the geographic market per the Capps (2003) model. However, patients may be more or less willing to select a hospital based on not only the travel time but how urgent their condition is, as indicated by whether the admission is scheduled or unscheduled and the nature of the condition—for example, a cancer patient may be more willing and able to travel farther to a hospital that offers a certain type of cancer treatment than a patient with a heart attack.
 - Base Model: No interaction.
 - Test: Interact admission through the emergency room with travel time, and admissions with a primary diagnosis of cancer and travel time.

- Payer mix
 - Rationale: The Conditional Choice model treats the hospital market as an “option demand” market in which managed care organizations negotiate with hospitals for contracts to provide care on behalf of customer/members. Contracts determine which local hospitals are included in the network and the payment obligations of the plan. Consumers (or employers as their representative) then decide which network to join. However, for government payers reimbursement is based on a pre-existing methodology. For example, for Medi-Cal, existing law requires the department to develop and implement a Medi-Cal inpatient hospital reimbursement payment methodology based on diagnosis-related groups, subject to federal approval, that reflects the costs and staffing levels associated with quality of care for patients in general acute care

hospitals. Consequently, Medi-Cal providers generally cannot negotiate rates based on the market leverage of their facility. So we consider the model results with (1) commercial payers only and (2) all payers.

- Base Model: Private insurance and self-pay patients only.
- Test: Include private insurance, self-pay, and government payers.
- Service Offerings
 - Rationale: The service offerings dummies, S_j , that we include indicate whether the hospital specializes in specific service lines. However, service specialization is a field of study unto itself, and there is no single vetted approach to defining service specialization.²³ In all three case studies we discuss below, our product market is general acute care services; however, while general acute care (GAC) hospitals often offer many of the same services, some may “specialize,” however defined, in specific service offerings. To identify areas of specialization that may affect patient choice, we used two data sources. For 2011 we examined cardiac care, orthopedics, and cancer care and identified California hospitals “specializing” based on lists provided by the American Heart Association (AHA), the National Cancer Institute (NCI), and Becker’s Hospital Review of 101 hospitals with great orthopedic programs.^{24,25,26} These data were not readily available for 1998 and 2009, the analysis years for the other two case studies.

For 1998 and 2009 we relied on OSHPD hospital-reported data and looked at three areas of specialization: respiratory care, rehabilitation, and cardiovascular care. Based on an analysis of the data, we chose the cutoffs below for defining specialization in each area. We acknowledge that the criteria are arbitrary; however, it is our opinion that any definition using these criteria would be somewhat arbitrary. The cutoffs for the three areas are:

1. Respiratory care: Fewer than a dozen GAC hospitals had respiratory discharges; therefore, any hospital included in

²³ Conrad Kobel and Engelbert Theurl, “Hospitals Specialisation Within a DRG Framework: The Austrian Case,” *Working Papers in Economics and Statistics*, no. 2013-06 (June 2013), <https://www.econstor.eu/dspace/bitstream/10419/73871/1/2013-06.pdf>.

²⁴ Using the AHA data (<http://hospitalmaps.heart.org/AHAMAP/map/qimap.jsp>) we identified hospitals that participate in coordinated systems of care for ST-elevation myocardial infarction (STEMI) and meet standards listed at http://www.heart.org/HEARTORG/HealthcareResearch/Heart-Attack-Receiving-Center-Accreditation_UCM_439156_SubHomePage.jsp. Similarly, we used the AHA data to identify hospitals that specialize in heart failure.

²⁵ “101 Hospitals with Great Orthopedic Programs,” Becker’s Hospital Review, <http://www.beckershospitalreview.com/lists/101-hospitals-with-great-orthopedic-programs.html>.

²⁶ “Find a Cancer Center,” National Cancer Institute, <http://www.cancer.gov/researchandfunding/extramural/cancercenters/find-a-cancer-center>.

the model that had respiratory discharges was indicated as specializing in that area.

2. Rehabilitation care: Any hospital that had more than 50% of discharges from rehab or were in the top 10% of all hospitals in terms of total discharges was considered a rehabilitation specialty hospital.
 3. Cardiovascular care: Any hospital in the top 10% of all hospitals in terms of total cardiovascular (CV) surgeries was considered a CV specialty hospital.
- Base Model: Our base model had an indicator for teaching hospitals indicating that the hospital is likely a tertiary care center with specialty services and staff.
 - Test: Include additional indicators of specialization based on third-party data sources and OSHPD data for respiratory care, rehabilitation, and cardiovascular care as described above.

Other Model Specifications for Consideration

Below we address some questions raised by the model that were not addressed at all or were incompletely addressed by our sensitivity analyses.

Kaiser Hospitals

Competitive effects analysis in the past have sometimes excluded Kaiser hospitals based on the rationale that non-Kaiser hospitals compete only indirectly with Kaiser, since Kaiser is a vertically integrated healthcare provider that serves patients covered by its health plans. As such, health insurers could not choose a Kaiser facility as an alternative to another local hospital when forming their hospital networks. However, while it's true that non-Kaiser enrollees do not access Kaiser hospitals and that Kaiser enrollees do not access non-Kaiser hospitals, Kaiser's strong market power in California affects the bargaining process between a non-Kaiser hospital and another commercial insurer through insurer competition for enrollees. For this reason we included Kaiser hospitals in the model. Ho and Lee show that most hospitals negotiate lower prices when Kaiser is present, although very attractive hospitals (as measured by their expected utility contribution to an insurer's network) are still able to extract higher payments. Thus, while a Kaiser hospital may not be a viable immediate choice for a non-Kaiser patient, if it has high utility to the patient it may be that they would choose Kaiser during the next re-enrollment, and therefore we believe including Kaiser hospitals in the model is justified.

Given that Kaiser facilities were included in the model but Kaiser financial data are reported to OSHPD on a regional level, not an individual facility model, it was necessary to make some adjustments. Per Capps et al. property plant and equipment (PPE) per adjusted patient day is included in the model; however, PPE is missing for individual facilities. Therefore, the regional PPE was apportioned to individual Kaiser hospitals based on the number of licensed beds.

We had planned on testing the effects of Kaiser hospitals more directly by including a dummy variable for Kaiser hospitals. Doing so would allow us to observe how the fact that a hospital is part of the Kaiser system impacts patient hospital choice. However, after the data selection process had been completed, there were too few Kaiser hospitals in the data to conduct reliable analyses. For that reason we were unable to observe directly the impact of Kaiser hospitals on patient hospital choice using the selection model.

Readmissions

We examined 30 days vs. > 30 days readmissions; however, some readmissions are a normal part of care, such as return visits for physical therapy; some are due to entirely new health problems; and some are simply due to worsening of the disease. The 30-day unplanned readmission measures are estimates of unplanned readmission for any cause to any acute care hospital within 30 days of discharge from a hospitalization. CMS chose to rate hospitals based on unplanned readmissions within 30 days instead of over longer time periods (such as 90 days) because readmissions over longer periods may be affected by factors outside hospitals' control such as other complicating illnesses, patients' own behavior, or care provided to patients after discharge. Ideally, one would want to make a distinction between these various reasons for readmission regardless of the days that have elapsed, but this task is beyond the scope of this paper.

Narrow Networks

A caveat of the statistical selection model is that we cannot identify for certain the specific hospital choice set for each patient. For instance, as Gai explains, if an HMO payer restricts hospital choices, while Medicare does not, we might overstate the range of choices for the former from data including the latter.²⁷ If there is more than one HMO available locally, different HMO patients could potentially face different choices, and this model identifies the union of all HMO choices. The model is weakened somewhat in markets with narrow networks, made up of hospitals and physicians selected using cost and patient-outcomes criteria, where patient choice is more restricted. Insurers including Aetna and Health Net say narrower networks keep their exchange plan premiums affordable while still meeting the requirements of the Patient Protection and Affordable Care Act. Blue Cross and Blue Shield of Illinois says its exchange plans using narrow networks will cost 20% to 30% less than its exchange plans with bigger networks.²⁸ The impact of narrow networks has been small so far, as they are mostly associated with some new public exchange plans.²⁹

²⁷ Yunwei Gai, "An Evaluation of Willingness-To-Pay Methods for Pre-Merger Investigation and Certificate of Need Licensing in Local Hospital Markets" (PhD diss., Florida State University, 2007), <http://diginole.lib.fsu.edu/cgi/viewcontent.cgi?article=1520&context=etd>.

²⁸ M. P. McQueen, "Less Choice, Lower Premiums," *Modern Healthcare*, August 17, 2013, <http://www.modernhealthcare.com/article/20130817/MAGAZINE/308179921>.

²⁹ Christopher Gearon, "Hospitals Get the Squeeze from Insurers' Narrow Networks," *US News and World Report*, April 10, 2014, <http://health.usnews.com/health-news/hospital-of-tomorrow/articles/2014/04/10/hospitals-get-the-squeeze-from-insurers-narrow-networks>.

Patient Price

The model does not include the price paid by the patient as a determinant of hospital choice since it is assumed to be the same across all hospitals (assuming they are all part of the patients' managed care network). However, to the extent that hospitals are "tiered," with material differences in copayments owed by the patients depending on which hospital is chosen, the price to the patient could be an important missing variable.

Distance vs. Travel Time

Our base model uses travel time, and travel time is preferable to distance since it more accurately reflects the level of effort required by the patient to get to any given hospital. However, travel distance is easier to generate. If both measures yield comparable results, using distance may more efficient, in terms of both cost and time in running the model. Therefore, an additional model specification could be running the model using (1) the distance between each zip code and hospital combination and (2) the travel time between each zip code and hospital combination.

Distance

While we examined distance from the patient zip code to the hospital zip code, we did not consider the extent to which distance might drive the hospital choice based on patient characteristics such as age, or severity of illness or type of illness (e.g., patients that are older might be less able or willing to travel greater distances to visit a hospital, and patients with less emergent conditions may be more able or willing to travel greater distances to visit a hospital), and such differences can be captured in the model by including the appropriate interaction terms as predictors.

Criteria for Inclusion of Zip Codes and the Number of Hospitals in the Model

The delineation of geographic markets can be fundamental to the determination of the degree of market power. Previous market power analyses—for example, those using the E-H test—started with the geographic market area delineation based on the patient flow criteria. This method tends to underestimate the merger's potential anticompetitive effects since it often overestimates the geographic market. The advantage of the selection model is that it is not based on a predefined geographic market. However, for example, including all the hospitals in the entire state of California and all the zip codes that contribute patients to those hospitals, regardless of the number, creates an unmanageably large dataset. Some authors have created cutoffs to eliminate zip codes that compose only a small portion of patients of the merging facilities. For example, in our analysis of UCSF / Children's Oakland affiliation, we kept all zip codes for which there were at least nine discharges for the two facilities. Our intent was to capture the zip codes that composed the largest patient pools up to approximately 92% of the patients from the two facilities. We then identified all hospitals with discharges in those zip codes and, if the total number of acute care discharges for a given hospital did not compose at least 2% of the total discharges for that hospital, then that hospital was deemed to be too small of a player in the relevant market and was removed from the analysis. Thus, we had a 92/2 selection criterion. In this case, however, the product market was focused on children's services, so there were fewer discharges. In cases involving GAC hospitals, there are far

more discharges, given that the product market is more expansive, and a 92/2 cutoff may not be possible due to limited computing resources. However, it is not clear whether or how weaker cutoffs affect the model results.

Public Payers

We grouped Medicare and Medicaid admissions together, and while they are both types of publicly provided insurance, they are not the same. Medicare patients may be unconstrained by narrow networks, which could affect commercial patients. Medicaid operates as a different type of publicly provided insurance, so testing the model with and without patients with Medicare or Medicaid separately may provide different results.

Diversion Ratios

When considering diversion ratios, due to restraints of time and computing resources we considered the diversion ratio in only one direction: the diversion of patients from the smaller facility to the larger, more predominant facility or system. However, it is relevant to consider what the models show about counterfactual patient flows in both directions when assessing whether there might be a problem. Therefore, for example, it is relevant to examine not only the diversion from Summit to Sutter but also from Sutter to Summit.

Patient Severity

As an alternative indicator of patient severity, in cases where the data are available, the model should include the patient severity weights.

Model Specifications

For ease of exposition, we have numbered the models that we ran using the following convention. The detailed specifications of each model described below can be found in the table in Appendix B.

- Model 1: The Base model.
- Model 2: Includes indicator if the admission was a readmission within 30 days of a previous admission.
- Model 3: All Medicare and Medi-Cal (Medicaid) discharges included, along with private insurance and self-pay discharges.
- Model 4: Interaction terms of patient travel time to the hospital with entry to the hospital through the ER and patient travel time to the hospital with a patient primary diagnosis of cancer.
- Model 5: Alternative data on hospital specialties interacted with patient characteristics.

Other Considerations

Computing Resources

- Issue of limitations on computing capacity.
 - Computing resources consisted of a virtual server with 64 GB of RAM and 100 GB of disk space.
 - Approximately 98 million records created by combining each discharge with each hospital using the described hospital selection criteria.
- The dataset used for the analysis is created by combining patient data contained in each discharge with hospital characteristics for each hospital included in the analysis. Thus, if we start with m discharges and n hospitals, the final dataset will contain $m \times n$ rows of data. For example, if the selection criteria were to result in 50 hospitals with 300,000 discharges, the final dataset would consist of 15 million rows of data. With more than 3 million acute care discharges, excluding duplicate claims for newborns, and 305 acute care hospitals, a full dataset including all combinations of patient and hospital would approach 1 billion rows of data. Such large datasets can tax the computing resources of many organizations.
- The impact of this effect is more pronounced the greater the number of hospitals in the acquiring hospital system. This is because as more hospitals are in a system, the greater the reach of the system in terms of the number of zip codes that make up 80% (or other cutoff described above), leading to more hospitals being included in the dataset, leading to a greater number of discharges included in the dataset. As a result of our work, we arrived at a rough rule of thumb for working with the California discharge data: there will be approximately 10,000 to 15,000 rows of data in the final dataset for analysis for every five hospitals in the acquiring system.

Three Case Studies

We chose three past hospital mergers in California reviewed by the California attorney general in order to consider the impact of the selection model relative to (1) the methodology used at the time the regulatory agencies reviewed the merger and (2) alternative approaches for specifying the model. The three mergers include:

- St. Joseph / Hoag, approved in 2013
- Victor Valley Community Hospital / Prime, denied in 2011
- Summit/Sutter, approved in 1999

The three mergers were selected somewhat arbitrarily, but we chose two relatively recent mergers and an older merger, the Summit/Sutter case, since this latter case (1) went to court and both the defendants and plaintiffs presented findings of their competitive effects analysis using the E-H test, the prevailing methodology at the time, (2) the authors of this paper had previous experience with this case as consulting experts, and (3) there have been several post-merger analyses of the effects of this merger. St. Joseph / Hoag and Victor Valley / Prime were not reviewed by the California attorney general's Anti-

trust Law Section but by the Charitable Trusts Section. The Attorney General Charitable Trusts Section reviews transactions for their impact on charitable assets and the accessibility and availability of healthcare services in the service area. However, in considering whether to consent to any such transfer of ownership, the attorney general must also consider whether the effect of the transaction may be to substantially lessen competition or lead to a monopoly.

For each of the mergers, we briefly describe (1) the background of the merger, (2) the decision and the basis for the decision by the regulatory agency, and (3) the results from the selection model and whether they supported the previous decision by the regulatory agency.

St. Joseph/ Hoag

In 2012 Hoag Memorial Hospital Presbyterian, a California nonprofit public benefit corporation, requested the California attorney general's consent to enter into an affiliation with St. Joseph Health System (SJHS), a California nonprofit public benefit corporation. Hoag, a hospital in Newport Beach with 484 licensed beds, provided inpatient, outpatient, and emergency services for the residents of Orange County, California. Hoag also operated a second hospital, Hoag Hospital Irvine, licensed for 84 beds. In addition to the two acute care hospitals, Hoag also had seven health centers and five urgent care centers. Hoag Hospital Newport Beach, which has served Orange County since 1952, and Hoag Hospital Irvine, which opened in 2010, were both designated magnet hospitals by the American Nurses Credentialing Center.³⁰

Both Hoag and SJHS were similar in that both were nonprofit, faith-based organizations with similar missions, moral concerns, objectives, and commitments for providing healthcare services. The transaction consolidated control over operations and strategy for the five St. Joseph hospitals and two Hoag hospitals under the new system, Covenant Health Network. According to the attorney general's advisor, the transaction was not due to the financial insolvency of the hospital: "[Hoag's] affiliation is not being driven out of a near-term financial or strategic necessity."³¹

The report prepared for the attorney general defined Hoag's service area as composed of 45 zip codes, from which approximately 81% of Hoag's discharges originated in 2011.³² Nearly 50% of Hoag's discharges were from the top 11 zip codes, located in Newport Beach, Huntington Beach, Irvine, Costa Mesa, and Fountain Valley. Hoag's market share in this service area was approximately 17% in 2011, with Saddleback Memorial Medical Center and Mission Hospital Regional Medical Center ranked second in inpatient discharges with approximately 10% market share, and all of Kaiser with an 8.1% market

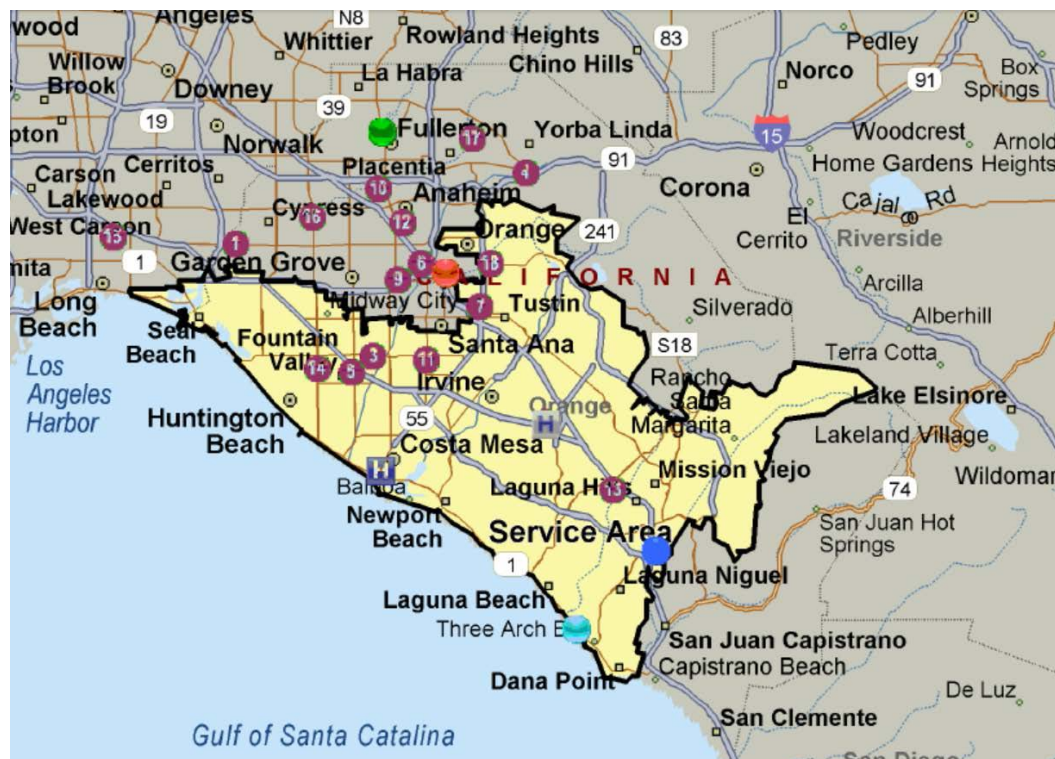
³⁰ "Hoag and St. Joseph Health Complete Historic Health Care Affiliation," St. Joseph Health, February 28, 2013, <http://www.stjhs.org/SJH-Newsroom/Announcements/2013/HOAG-AND-ST-JOSEPH-HEALTH-COMplete-HISTORIC-HEAL.aspx>.

³¹ Tom Egan, "Commentary: Hoag Should Unwind Affiliation with St. Joseph," *Daily Pilot*, October 14, 2013, http://articles.dailypilot.com/2013-10-14/opinion/tn-dpt-me-1016-commentary1-20131014_1_hoag-hospital-hoag-and-st-attorney-general.

³² *Effect of the Affiliation of Hoag Memorial Hospital Presbyterian with St. Joseph Health System on the Availability or Accessibility of Healthcare Services*, Medical Development Specialists, December 28, 2012, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/hoag_impact.pdf.

share. The map below, as submitted to the California attorney general, shows Hoag's service area as defined by the authors of the report, with approximately 1.6 million residents and nine other hospitals located within Hoag's service area (Figure 1).

Figure 1. SJHS/Hoag Service Area



- Hoag Memorial Hospital Presbyterian
- Hoag Hospital Irvinemore
- Mission Hospital Laguna Beach
- St. Joseph Hospital - Orange
- St. Jude Medical Center
- Mission Hospital Regional Medical Center
- Los Alamitos Medical Center
- Hoag Orthopedic Institute
- Fountain Valley Regional Hospital and Medical Cent.
- Kaiser Anaheim
- Orange Coast Memorial Medical Center
- UC Irvine Medical Center
- Western Medical Center - Santa Ana
- Children's Hospital of Orange County
- Garden Grove Hospital and Medical Center
- Anaheim Regional Medical Center
- Coastal Communities Hospital
- Western Medical Center-Anaheim
- Saddleback Memorial Medical Center
- Huntington Beach Hospital
- Long Beach Memorial Medical Center
- West Anaheim Medical Center
- Placentia-Linda Community Hospital
- Chapman Medical Center

Source: *Effect of the Affiliation of Hoag Memorial Hospital Presbyterian with St. Joseph Health System on the Availability or Accessibility of Healthcare Services*, Medical Development Specialists, December 28, 2012, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/hoag_impact.pdf.

As with other Charitable Trusts reports, this one focused on availability of services and not on a rigorous definition of market or assessment of competitive effects. However, a quick calculation of the HHI, the sum of the squares of the market shares, shows a post-merger HHI below 500. The agency regards markets with a post-merger HHI under 1,000 as indicative of an unconcentrated market. Mergers resulting in unconcentrated markets are unlikely to have adverse competitive effects and ordinarily require no further analysis.

The transaction was ultimately approved, and The George Hoag Family Foundation finalized the deal to create a new health system that would consolidate control over operations and strategy for five St. Joseph hospitals and two Hoag hospitals under the new system, Covenant Health Network.

Victor Valley Community Hospital/ Prime

In September 2010 Victor Valley Community Hospital, an acute care hospital licensed for 101 beds, located in Victorville, California, filed for bankruptcy. KPC Global (KPC) beat out Prime Healthcare Services in an auction two months after the bankruptcy. KPC was approved, by then attorney general Jerry Brown, to buy the hospital, but KPC failed to seal the deal by the deadline in May 2011.³³ Prime then agreed to buy the hospital, but Attorney General Kamala Harris denied Prime's offer in September 2011, stating that the deal was not in the best interest of the community. This was in part based on an analysis through the California Attorney General's Charitable Trust Section responsible for reviewing and approving any sale or transfer of ownership or control of a material amount of assets of a nonprofit public benefit corporation that operates or controls a "health facility."³⁴

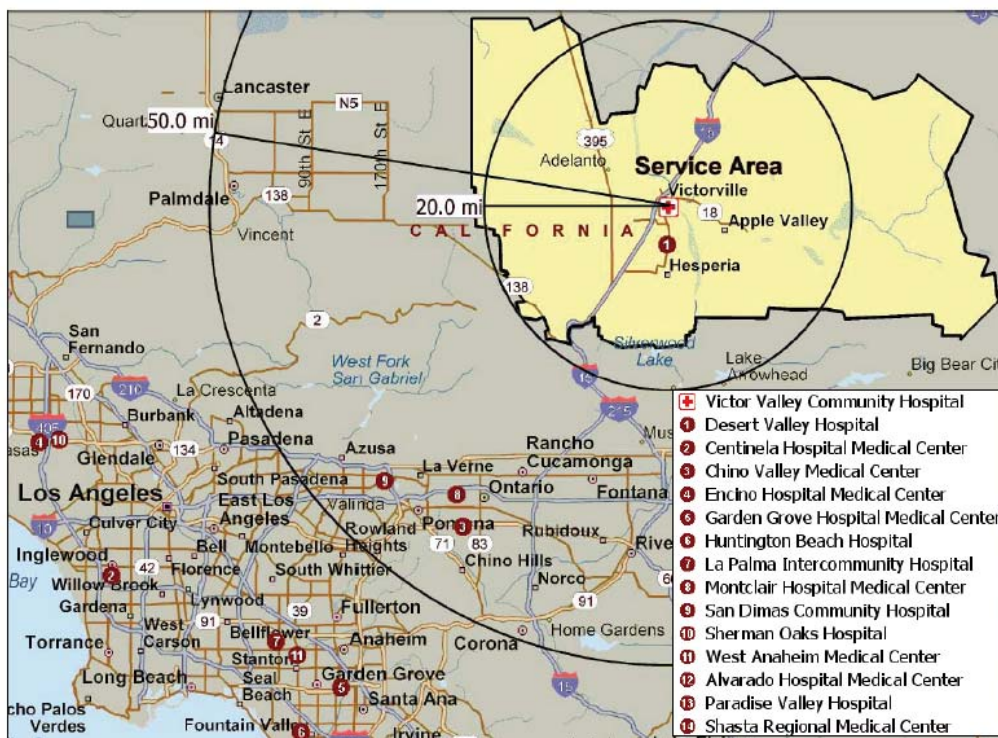
Generally, reports prepared for Charitable Trusts describe the possible effects that the proposed transaction may have on the delivery, accessibility, and availability of healthcare services in the service area. However, the service area definition in these reports is often cruder than that obtained through the more rigorous E-H or critical loss tests applied in court cases and is routinely based on some cutoff of discharges—for example, the zip codes that compose 90% of the discharges.

The map below from the California attorney general report provides information about hospitals owned by Prime Healthcare Services Inc. at the time the transaction was reviewed (Figure 2). The two other hospitals located within the hospital's service area included St. Mary's, with 186 licensed beds, and Desert Valley, with 83 beds. Desert Valley was the only hospital owned by Prime Healthcare Services Inc. that fell within the hospital's service area as defined by the authors of the report.

³³ Tomoya Shimura, "KPC Buys Victor Valley Community Hospital," *Victory Valley Daily Press*, October 15, 2012, <http://www.thekpcgroup.com/news/kpc-buys-vvch.pdf>.

³⁴ A "health facility" as defined in the Health and Safety Code section 1250.

Figure 2. Victor Valley Service Area



Source: *Effect of the Acquisition by Prime Healthcare Services Foundation Inc. of Victor Valley Community Hospital on the Availability or Accessibility of Healthcare Services, Medical Development Specialists*, August 5, 2011, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/vvch_impact_2011.pdf.

In the Victor Valley analysis prepared by consultants for Charitable Trusts, the focus was on continued access to and availability of services for the community. However, their final report also included information on market shares for the facilities involved in the transaction based on a zip code analysis. The report defined the hospital's service area as a set of 11 zip codes from which the hospital had approximately 86% of its discharges based on 2009 data, where 86% was a somewhat arbitrary cutoff. The service area defined as such yielded a hospital market share of just 15.5% for Victor Valley. The only hospital in the designated market area for Victor Valley that was owned by Prime was Desert Valley Hospital. The combined market share of Victor Valley and Desert Valley was 29.5%, less than that of the hospital with the highest market share, 36.5%, in the market area. The analysis concluded that Prime would be "... likely to continue the availability and accessibility of healthcare services at the Hospital. In general, it is expected that access for Medicare, Traditional Medi-Cal, and patients other than Third-Party Managed care will remain unchanged. Furthermore, the Purchaser's capital investment over the next five years should lead to substantial improvement to facilities, in-

frastructure, and certain services at the Hospital.”³⁵ The authors concluded that if the California attorney general approved the proposed transaction, which it did not, certain conditions would be required to minimize potential negative health impacts that might result from the transaction—for example, that the hospital continue as a general acute care facility for five years and specific basic community services such as ob/gyn be continued. While the analysis did not seem to discourage the transaction, ultimately, in September 2011 the attorney general denied the sale of Victor Valley Community Hospital to Prime Healthcare Services, saying it was not in the public interest and “will likely create a significant effect on the availability or accessibility of healthcare services in the affected community.”³⁶ It is important to note here, however, that the decision focused on service availability and not on the competitive effects of the merger. However, a quick calculation of the HHI, the sum of the squares of the market shares, for the market area as defined in the attorney general report, shows a post-merger HHI of 2,415 with an increase of more than 400 points from the pre-merger HHI. Based on 2010 Guidelines, the agencies consider markets “highly concentrated” at an HHI of 2,500 or greater. A merger producing (1) an increase of more than 200 HHI points and (2) a post-merger HHI exceeding 2,500 will be presumed anticompetitive. The thresholds for the 2010 Guidelines, however, do not represent a loosening of horizontal merger review standards from the earlier Guidelines but instead conform the Guidelines to the thresholds that the agencies have most often used in practice. Thus, the Victor Valley merger was just below the anticompetitive threshold.

While the merger was denied based on information unrelated to the HHI, nonetheless, in an effort to salvage the bankrupt hospital, the hospital’s board continued talks with Prime. Ultimately, however, Victor Valley Community Hospital agreed to a \$33.8 million purchasing offer by Riverside-based KPC Global medical group, and the agreement was approved at the federal bankruptcy court in Santa Ana, California.

Summit/Sutter

On August 10, 1999, the California attorney general filed suit in federal court to block the merger of Summit Medical Center in Oakland with Alta Bates Medical Center, owned by Sutter Health in Berkeley. The suit was based on the attorney general’s belief that the merger would result in one hospital chain dominating hospital services and dictating healthcare prices in the East Bay.³⁷ The state action was filed under Section 7 of the federal Clayton Act, which prohibits any merger or acquisition where the effect of such acquisition may be to substantially lessen competition or lead to a monopoly.

³⁵ *Effect of the Acquisition by Prime Healthcare Services Foundation Inc. of Victor Valley Community Hospital on the Availability or Accessibility of Healthcare Services*, Medical Development Specialists, August 5, 2011, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/vvch_impact_2011.pdf.

³⁶ Acting chief deputy California attorney general Michael Troncoso, letter to Charles Slyngstad, September 20, 2011, http://ag.ca.gov/charities/pdf/vvch_decision_2011.pdf.

³⁷ “Attorney General Lockyer Files Antitrust Suit to Block Merger of Summit-Sutter / Alta Bates Medical Centers” (Press Release), California Dept. of Justice, August 10, 1999, <http://oag.ca.gov/news/press-releases/attorney-general-lockyer-files-antitrust-suit-block-merger-summit-sutteralta>.

Following a lengthy trial, the US District Court allowed the merger to proceed based on its opinion that Summit was a failing firm and its rejection of the plaintiffs proposed geographic market.³⁸ The plaintiffs – that is, the state – hypothesized an “inner East Bay” geographic market, and based on their definition of the product and geographic market, they calculated a post-merger market share of almost 50% based on supply-side market share calculations. However, the defendants argued that the relevant geographic market extended throughout the Bay Area and beyond (including San Francisco, San Jose, and counties across the hills east and south of Oakland), relying on the 90% service area of the merging hospitals. The defendants’ market share calculations, with a broader geographic market, resulted in a much lower estimate of the post-merger market share of the merging hospitals. The court ultimately ruled in favor of the merging parties, stating that “the Court finds a service area based on the 90% level of significance . . . to be more appropriate than one based on an 85% threshold as proposed by plaintiff.”³⁹ Courts have generally acknowledged the 90% level of significance.⁴⁰ However, there is no clearly articulated economic rationale for 90%. Upon appeal, the Ninth Circuit upheld the District Court’s decision to let the merger proceed, and Sutter completed its acquisition of Summit at the end of 1999.

In 2002, then FTC chairman Timothy Muris announced the Merger Retrospectives Project, which involved selecting a handful of consummated mergers to determine their actual competitive effects. One of these mergers was Summit/Sutter, and an analysis by Steve Tenn of the FTC found that the merger between Sutter’s Alta Bates Medical Center and Summit Medical Center caused prices to increase significantly, suggesting that the merger may have reduced consumer welfare and harmed competition. In particular, Tenn found that the prices at Summit rose 23.2% to 50.4% against its peers, which was among the largest increase in California.⁴¹ His findings questioned the applicability of the Elzinga-Hogarty method for delineating the geographic market in which to analyze a transaction, the approach both sides relied on in the preliminary injunction trial. He asserted that his results confirmed that substantial patient flows across two geographic areas, the basis for the E-H test, was insufficient to conclude that competition from hospitals in one area will prevent a post-merger price increase in the other. (It is important to note that there was concern that if Sutter did not purchase Summit, the hospital’s poor situation may have led it to exit the market completely.)⁴² Subsequently, we consider here whether the statistical selection model would have influenced the court’s decision differently.

³⁸ California v. Sutter, 130 F Supp. 2d. 1109 (N.D. Cal. 2002).

³⁹ Ibid.

⁴⁰ Ibid.

⁴¹ Steven Tenn, “The Price Effects of Hospital Mergers: A Case Study of the Sutter-Summit Transaction,” Federal Trade Commission Working Paper, no. 293 (November 14, 2008), https://www.ftc.gov/sites/default/files/documents/reports/price-effects-hospital-mergers%2%A0-case-study-sutter-summit-transaction/wp293_0.pdf.

⁴² Ibid.

Summary and Conclusions for All Three Case Studies

The diversion ratio, by itself, does not provide an indication of the impact that a merger or affiliation agreement would have on prices, and it must be interpreted in the context of other information about the transaction. While the merger Guidelines do not specify diversion ratio thresholds, some sources have identified diversion ratios greater than 14.3% being interpreted as indicative of competition concerns.^{43,44} While the diversion ratio is an important indicator, it is generally used as one of several indicia to assess likely competitive effects. The diversion ratios for the various models in each of the three case studies were comparable, suggesting that the model is relatively robust. However, it is worth noting that we looked at a limited number of model variations due to time and computing restraints, and other changes in the model specifications may have yielded different results.

SJHS/Hoag – For the SJHS/Hoag transaction, the results of the base model specification yield a diversion ratio of 28%, suggesting that the SJHS system hospitals are the closest substitute to Hoag for 28% of the discharges (Table 2). The other model specifications are slightly lower, ranging from 21% to 28% for the system hospitals considered collectively. As we consider the implications for this value, interpretation of whether this would raise regulatory agency concerns is not guided by explicit benchmarks or ranges. There is no bright-line test for diversion ratios, as noted by the Horizontal Merger Guidelines: “Diversion ratios between products sold by one merging firm and products sold by the other merging firm can be very informative for assessing unilateral price effects, with higher diversion ratios indicating a greater likelihood of such effects.” However, the diversion ratios indicate that, on average, about one in four of the Hoag discharges find SJHS hospitals the closest substitutes.

Table 2. Diversion Model Summaries: SJHS/Hoag

Diversion Model Summaries: SJHS/Hoag	
Run	Diversion Ratio
Diversion 5	0.21
Diversion 4	0.28
Diversion 3	0.24
Diversion 2	0.27
Diversion 1	0.28

Diversion 1: Individual SJHS Hospital Diversion Ratios	
Hospital Name	Diversion Ratio
St. Joseph Hospital–Orange	0.17

⁴³ Chris Walters, “Approximating Diversion Ratios for Retail Chain Mergers” (presented to CRESSE European Conference on Competition & Regulation, July 5, 2008), <http://www.cresse.info/uploadfiles/Chris%20Walters.pdf>.

⁴⁴ *Diversion Ratios: Why Does It Matter Where Customers Go If a Shop Is Closed?*, Oxera, February 2009, <http://www.oxera.com/Oxera/media/Oxera/downloads/Agenda/Diversion-ratios.pdf>.

Mission Hospital Regional Medical Center	0.07
St. Jude Medical Center	0.03
St. Mary Medical Center	0.02
Total	0.28

Looking more closely at the individual SJHS hospitals, the highest diversion ratio for the SJHS hospitals is the St. Joseph–Orange hospital at 16.8%, followed by Mission Hospital Region Medical Center at 6.5%. It is interesting to note that the attorney general report on the SJHS/Hoag transaction found that the SJHS Mission Hospital Regional Medical Center consistently ranked third in inpatient discharges relative to Hoag in the attorney general report’s designated market area while St. Joseph–Orange ranked sixth.⁴⁵ So the relative importance of these two hospitals is inverted based on the two different approaches of looking at the transaction.

For two models the diversion ratio varied 5% or more from the base model. One is model 9, where we included additional indicators for hospital specialization from industry organizations AHA and Becker, discussed in more detail above. There is a strong argument for excluding discharges covered by Medicare and Medicaid, since these payers do not have the same freedom or leverage to negotiate prices as commercial payers do and act more as price takers, which is why they are excluded from the base model. However, if a hospital has a large percentage of Medicare/Medicaid patients and a very small percentage of commercially covered patients, then including all payers may still serve as a useful exercise in understanding which hospitals are close substitutes. In the SJHS/Hoag models that include Medicare/Medicaid patients, the ratio drops by 15% to 24% compared to the base model diversion ratio of 28%. Similarly, the ratios for the two closest SJHS competitors, St. Joseph–Orange and Mission Hospital Regional Medical Center, drop to 13.8% and 6.0%, respectively. Including information on specialization generates a diversion ratio 23% lower than the base model. (However, specialization for this model is based on self-reported data to OSHPD, not an industry organization report as in the Victor Valley report.) This seems consistent with the theoretical construct of the model, since additional detailed data on specialization would allow the hospital to distinguish itself from other area hospitals.

Victor Valley / Prime – As with SJHS/Hoag, the fact that the diversion ratios from the models we ran for the Victor Valley / Prime transaction were comparable with one exception suggests that, based on the alternative model specifications we ran, the model is relatively robust. The diversion ratio for the base model of 50% between Victor Valley and the Prime system hospitals, taken as a whole, reflects the percentage of Victor Valley patients that would switch to a Prime system hospital (Table 3). As we consider the implications for this value, interpretation of whether this would raise regulatory agency concerns is not guided by explicit benchmarks or ranges, and as discussed above, there is no bright-line test. However, the diversion ratio indicates that almost half of Victor Val-

⁴⁵ *Effect of the Affiliation of Hoag Memorial Hospital Presbyterian with St. Joseph Health System on the Availability or Accessibility of Healthcare Services*, Medical Development Specialists, December 28, 2012, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/hoag_impact.pdf.

ley’s patients find Prime hospitals the closest substitutes, suggesting they are very close competitors.

Table 3. Diversion Model Summaries: Victor Valley / Prime

Diversion Model Summaries: Victor Valley / Prime	
Run	Diversion Ratio
Diversion 5	0.53
Diversion 4	0.49
Diversion 3	0.34
Diversion 2	0.50
Diversion 1	0.50

Diversion 1: Victor Valley to Prime Hospitals- Top Ten	
Hospital Name	Diversion Ratio
Desert Valley Hospital	0.46
Montclair Hospital Medical Center	0.01
Centinela Hospital Medical Center	0.00
Chino Valley Medical Center	0.00
Encino Hospital Medical Center	0.00
Garden Grove Hospital And& Medical Center	0.00
Huntington Beach Hospital	0.00
La Palma Intercommunity Hospital	0.00
San Dimas Community Hospital	0.00
Sherman Oaks Hospital & Health Center	0.00
West Anaheim Medical Center	0.00
Total	0.47

The 2011 report prepared for the California Attorney General’s Charitable Trust Section indicated that Desert Valley, located within five miles of Victor Valley, was the only hospital owned by Prime Healthcare Services that fell within the hospital’s service area.⁴⁶ Looking more closely at the individual Prime hospitals, the diversion ratio for that one hospital, Desert Valley, is 46%, comprising 96% of the Prime System diversion ratio that reflects the total diversion ration for all included Prime hospitals. This suggests that there is a high degree of substitutability between the two hospitals.

In two models, the diversion ratio varied 5% or more from the base model. One is model 9, where we included additional indicators for hospital specialization from industry organizations AHA and Becker, discussed in more detail above. The diversion ratio was

⁴⁶ *Effect of the Acquisition by Prime Healthcare Services Foundation Inc. of Victor Valley Community Hospital on the Availability or Accessibility of Healthcare Services*, Medical Development Specialists, August 5, 2011, http://oag.ca.gov/sites/all/files/agweb/pdfs/charities/pdf/vvch_impact_2011.pdf.

45% for Desert Valley, slightly lower than that of the base model and, like the base model, 96% of the diversion ratio for all included Prime system hospitals.

The other is model 5, where we included Medicare and Medicaid claims. As in SJHS/Hoag, there is a strong argument for *excluding* discharges covered by Medicare and Medicaid, since these payers do not have the same freedom or leverage to negotiate prices as commercial payers do and act more as price takers, which is why they are excluded from the base model. Like SJHS/Hoag the diversion ratio decreased if these discharges are included, and in the case of Victor Valley / Prime the diversion ratio decreases by a third to 34% for Desert Valley Hospital, suggesting that approximately one-third of patients consider Desert Valley the closest substitute for hospital services rather than 50% if these patients are included.

It is interesting to note that the diversion ratio was slightly lower when additional measures of specialization were included, suggesting that specific service even in GAC hospitals may provide some differentiation for patients.

The diversion ratios for the models, except the one that includes Medicare and Medicaid patients, suggest that close to half of patients would choose Desert Valley if they had to select a hospital other than Victor Valley. Had the California attorney general used this model and any of the model variations to evaluate the transaction, it is unlikely that the attorney general’s decision to deny the merger would have changed.

Summit/Sutter – As with the other two case studies, the fact that the diversion ratios from the models we ran were comparable, with one exception, suggests that, based on the alternative model specifications we ran, the model is relatively robust. The model for Sutter/Summit was necessarily limited since the data did not contain the same elements as the more recent data. For example, we had to exclude Kaiser hospitals since we were not able to get OSHPD financial data for these facilities, even by region, which was a part of the base model.

The diversion ratio for the base model of 24% between Summit and Sutter system hospitals, taken as a whole, reflects the percentage of Summit patients that would switch to a Sutter system hospital (Table 4). Alta Bates, the Sutter hospital that was the closest competitor based on previous analyses and our current model, had a diversion ratio of 11%, indicating that 11% of Summit patients would go to Alta Bates. Another Sutter Bay Area hospital was California Pacific Medical Center, with a diversion ration of 6%. The next closest competitor was Medical Center at University of California San Francisco (UCSF) hospital, UCSF / Mt. Zion, and San Francisco General Hospital, with a combined diversion ratio of 19%. Diversion ratios for Summit patients to Alta Bates and other area Sutter hospitals for the other choice models we ran ranged from 21% to 22%.

Table 4. Diversion Model Summaries: Summit/Sutter

Diversion Model Summaries: Summit/Sutter	
Run	Diversion Ratio
Diversion 5	0.23
Diversion 4	0.22

Diversion Model Summaries: Summit/Sutter	
Run	Diversion Ratio
Diversion 3	0.22
Diversion 2	*
Diversion 1	0.24

*Data for readmissions was not available

Diversion 1: Summit to Sutter Hospitals- Top 10	
Hospital Name	Diversion Ratio
ALTA BATES MEDICAL CENTER - ASHBY CAMPUS	0.11
CHILDREN'S HOSPITAL MED CENTER OF NO. CALIFORNIA	0.11
ALAMEDA CO MED CTR - HIGHLAND CAMPUS	0.09
MEDICAL CTR AT THE U.C.S.F.	0.09
SAN FRANCISCO GENERAL HOSPITAL	0.07
PACIFIC CAMPUS HOSPITAL	0.06
DOCTORS MEDICAL CENTER - SAN PABLO CAMPUS	0.05
ST. MARY'S MEDICAL CENTER, SAN FRANCISCO	0.05
ALAMEDA HOSPITAL	0.05
UCSF/MOUNT ZION	0.03
Total	0.71

Consideration of whether this would raise regulatory agency concerns is not guided by explicit benchmarks or ranges, and there is no bright-line test for diversion ratios, as noted earlier. However, a diversion ratio of 24% to Sutter hospitals does not clearly raise a red flag in and of itself.

Interpretation of the diversion ratio may also be considered in the context of its implications for post-merger pricing. While a high diversion ratio between a pair of hospitals is an indication of the hospitals being close substitutes, diversion ratios incorporated into the UPPI model, formulated by Farrell and Shapiro, provide a measure of the combined firm's incentive to increase prices post-merger.⁴⁷ The UPPI uses three key inputs: the diversion ratios, the pre-merger gross margins, and an estimate of or assumption about the likely efficiencies stemming from the merger.

⁴⁷ Joseph Farrell and Carl Shapiro, "Antitrust Evaluation of Horizontal Mergers: An Economic Alternative to Market Definition," *B.E. Journal of Theoretical Economics* 10, no. 1 (2010), http://www.researchgate.net/publication/46556520_Antitrust_Evaluation_of_Horizontal_Mergers_An_Economic_Alternative_to_Market_Definition.

Table , developed by Ramanarayanan, calculates the critical diversion ratios for various values of the contribution margin under the assumption that the merger generates a marginal cost savings (or efficiencies) of 10%.⁴⁸

The table suggests that if a hospital’s contribution margin is 50% (as is typically the case for the hospital industry), the diversion ratio would have to be no larger than 20% for the transaction to not be presumptively anticompetitive. The smaller the contribution margin, the larger the diversion ratio needs to be to raise anticompetitive concerns. A merger screen based on UPPI only estimates the strength of the incentive of the merged firm to raise prices but does not actually measure the magnitude of the increase in price if an increase is projected by the model.⁴⁹

Table 5. Critical Diversion Ratios for Various Values of Contribution Margin

Contribution Margin	Critical Diversion Ratio
40%	25%
50%	20%
60%	16.7%

Using model 1 for our three case studies in the SJHS/Hoag transaction, we had a diversion ratio of 28%, suggesting that a margin slightly lower than 40%, assuming 10% efficiencies, would raise concerns. Using model 1 in the Victor Valley / Prime transaction, we had a diversion ratio of 50%, suggesting that a margin much lower than 40%, assuming 10% efficiencies, would raise concerns. Using model 1 in the Summit/Sutter transaction, we had a diversion ratio of 24%, suggesting that a margin of about 40%, assuming 10% efficiencies, would raise concerns.

Originally, we considered using the OSHPD hospital annual financial data to calculate the contribution margin to assess whether the diversion ratio was critical; however, several issues came to our attention. There are concerns that the GUPPI is a useful concept but isn’t appropriate for hospitals where patients rely heavily on insurance to cover a portion of their costs. Also, the UPPI model in the Farrell and Shapiro paper uses a 0.5 multiplier that captures how the upward pressure might be expected to be passed through to final retail prices, and this multiplier is consistent with a linear demand system but not with other, more commonly applied ones (log linear, AIDS, logit). Finally, there are concerns that the publicly reported margins are quite different from those backed out in the most recent academic literature trying to assess actual marginal costs for hospitals.⁵⁰

⁴⁸ Subramaniam Ramanarayanan, *Diversion Analysis as Applied to Hospital Mergers: A Primer*, NERA Economic Consulting Group, June 24, 2014, http://www.nera.com/content/dam/nera/publications/archive2/PUB_Diversion_Analysis_Hospital_Mergers_0614.pdf.

⁴⁹ Ibid.

⁵⁰ Gautam Gowrisankaran, Aviv Nevo, and Robert Town, “Mergers When Prices Are Negotiated: Evidence from the Hospital Industry,” *American Economic Review* 105, no. 1 (2015): 172-203, doi:10.1257/aer.20130223.

SUMMARY AND CONCLUSIONS

Anticompetitive transactions among hospitals and other competitive entities that lead to higher prices without offsetting efficiencies and quality enhancements are targets of the US DOJ and FTC, which are charged with protecting consumer interests. The DOJ and FTC have challenged what they considered anticompetitive mergers among hospitals over the past 15 years, but until the Evanston / Northwestern Healthcare decision, the DOJ and FTC have not succeeded in convincing the court, losing at least six consecutive court battles. Challenges to consolidation of other providers, including local physician medical practices, have been equally unsuccessful.

The courts' acceptance of methods for geographic market definition, based primarily on patient flow data and focusing largely on the Elzinga and Hogarty (E-H) and critical loss methodologies, is a principal contributor to the agencies' losses. These methods often define expansive geographic markets, particularly for urban areas, in which the merging parties have market shares too small to warrant interference from the courts. While DOJ and FTC economists argued that these methods lacked theoretical and empirical foundations supported by published academic studies, the courts continued to accept flow analysis. However, with the admission by Ken Elzinga that the E-H approach he helped develop was flawed, and with the introduction of the conditional logit choice model that did not rely on patient flows to establish a predefined geographic market, regulatory agencies' cases were more persuasive. Hospital antitrust cases hinge on establishing whether the defendant hospital has market power, and the selection model is predicated on assessing market power based on an understanding of the relationship between hospital characteristics and patient needs independent of the pre-established geographic market area. Information on this relationship reveals the closest competitors to a given hospital as indicated by the diversion ratio. The model, however, is not rigid and has leeway for modifications based on the hospitals involved in the transaction and some discretion of the analyst.

The purpose of our analysis was to better understand (1) how sensitive the selection model results were to alternative model specifications as reflected by the diversion ratios and (2) whether, if the selection model had been applied in three previous California hospital consolidations, the model results may have changed the California attorney general's decision to approve or deny the transactions.

In general, we found that the model was relatively robust to alternative variable definitions and model specifications within each case study. The two model changes that had the largest impact were the additional alternative measures of specialization and the inclusion of Medicare and Medicaid discharges. The specialization measures impacted the model similarly for all case studies by lowering the diversion ratios. On the other hand, the inclusion of the Medicare/Medicaid discharges increased the diversion ratios to different degrees depending on the transaction, thereby providing an indicator for the increased likelihood of unilateral price effects.

While theoretically, the conditional logit choice model has clear advantages over the patient flow methodologies previously used in court cases, it is not clear whether, had this

methodology been applied when the three case studies we examined were initially reviewed by the California attorney general, there would have been different outcomes.

Some questions raised by our analysis include:

What are the implications of a large diversion ratio for a competitor resulting from the merger? Agencies may need to be watchful in cases where the transaction results in a large proportion of patients finding a competing hospital to be the closest substitute. While a merger may not create market power for the entities involved, it may give a competing hospital or hospital system the leverage to negotiate higher prices without compensating benefits to patients.

What are the implications for geographic regions with overcapacity? Some areas of California and the US have been documented as having excess hospital bed capacity. Some hospitals are exploring various transactions and consolidations to help adjust overall inpatient capacity to better meet current needs while preparing for changes resulting from recent healthcare reforms. Generally, financially stronger hospitals are considering partnerships with other well-located hospitals with good payer mixes, and the financially stronger, larger hospitals are interested in working with smaller hospitals to either expand their capacity with a wider range of services or increased bed capacity. Meantime, the smaller, struggling hospitals need financial support to invest in capital improvements, particularly if they have not yet met seismic requirements.⁵¹ Regulatory agencies will be faced with challenges when the demand may not exist for multiple hospitals in an area or a financially failing hospital that serves vulnerable populations needs a partner, but consolidation would likely result in significantly higher prices charged by the merged firms.

Agencies will also be challenged with the increasing complexity of relationships between various types of providers to provide integration and a continuum of care for population health. Implementing the selection model may require some additional tweaking to account for various provider types based on the types of services they offer.

⁵¹ *Los Angeles: Fragmented Health Care Market Shows Signs of Coalescing*, California HealthCare Foundation, January 2013, <http://www.chcf.org/publications/2013/01/regional-market-los-angeles>.

APPENDIX A: HOSPITAL TRANSACTION CASE STUDY HOSPITALS

St. Joseph/Hoag Hospital Transaction

St. Joseph Hospitals in California Included

- Mission Hospital Regional Medical Center
- St. Joseph Hospital-Orange
- St. Jude Medical Center
- St. Mary Regional Medical Center

Victor Valley/Prime Hospital Transaction

Prime Hospitals in California Included

- Alvarado Hospital
- Centinela Hospital Medical Center
- Desert Valley Hospital – the Prime facility closest to Victor Valley
- Encino Hospital Medical Center
- Garden Grove Hospital & Medical Center
- Huntington Beach Hospital
- La Palma Intercommunity Hospital
- Montclair Hospital Medical Center
- Paradise Valley Hospital
- San Dimas Community Hospital
- Shasta Regional Medical Center
- Sherman Oaks Hospital & Health Center
- West Anaheim Medical Center

Prime Hospitals in California Excluded

These three hospitals were excluded based on their distant location from the hospitals involved in the transaction or because they did not provide the same types of services:

- Encino Hospital Medical Center
- Paradise Valley Hospital
- Shasta Regional Medical Center

Summit/Sutter Hospital Transaction

Sutter Hospitals in California Included

- Alta Bates Medical Center
- California Pacific Medical Center
- Novato Community Hospital
- Sutter Amador Hospital
- Sutter Auburn Faith Hospital

- Sutter Coast Hospital
- Sutter Davis Hospital
- Sutter Delta Medical Center
- Sutter General Hospital
- Sutter Lakeside Hospital
- Summit Medical Center-North Pavilion
- Sutter Medical Center of Santa Rosa
- Sutter Memorial Hospital
- Sutter Merced Medical Center
- Sutter Roseville Medical Center
- Sutter Solano Medical Center
- Sutter Tracy Community Hospital

Sutter Hospitals in California Excluded

These two facilities were not GAC hospitals, had a different product market, and were therefore excluded from the analysis:

- Sutter Center for Psychiatry
- Sutter Maternity & Surgery Center

APPENDIX B: MODELS

Variable Name/Definition	Base model	Hoag and Victor Valley						Summit/Sutter			
		Revised Base Model	Variation 04b	Variation 06b	Variation 08b	Variation 09b (Hoag)	Variation 09b (VV)	Revised Base Model	Variation 06b	Variation 08b	Variation 09b
forprofit	X	X						X			
teach	X	X						X			
ftesperadjacbedrn	X	X						X			
netppeperadjpatday	X	X						X			
thosp	X	X						X			
int0201 = forprofit*female	X	X						X			
int0202 = forprofit*agyradm	X	X						X			
int0203 = forprofit*rinc	X	X						X			
int0205 = forprofit*privcov	X	X						X			
int0206 = forprofit*selfpay	X	X						X			
int0207 = forprofit*mc	X	X						X			
int0301 = teach*female	X	X						X			
int0302 = teach*agyradm	X	X						X			
int0303 = teach*rinc	X	X						X			
int0305 = teach*privcov	X	X						X			
int0306 = teach*selfpay	X	X						X			
int0307 = teach*mc	X	X						X			
int0401 = ftesperadjacbedrn*female	X	X						X			
int0402 = ftesperadjacbedrn*agyradm	X	X						X			
int0403 = ftesperadjacbedrn*rinc	X	X						X			
int0405 = ftesperadjacbedrn*privcov	X	X						X			
int0406 = ftesperadjacbedrn*selfpay	X	X						X			
int0407 = ftesperadjacbedrn*mc	X	X						X			
int0501 = netppeperadjpatday*female	X	X						X			
int0502 = netppeperadjpatday*agyradm	X	X						X			
int0503 = netppeperadjpatday*rinc	X	X						X			
int0505 = netppeperadjpatday*privcov	X	X						X			
int0506 = netppeperadjpatday*selfpay	X	X						X			
int0507 = netppeperadjpatday*mc	X	X						X			
int0601 = transplant*female	X										
int0602 = transplant*agyradm	X										
int0603 = transplant*rinc	X										
int0605 = transplant*privcov	X										
int0606 = transplant*selfpay	X										
int0607 = transplant*mc	X										
int0701 = hosp_bed_lic_totl*female	X	X						X			

Variable Name/Definition	Base model	Hoag and Victor Valley						Summit/Sutter			
		Revised Base Model	Variation 04b	Variation 06b	Variation 08b	Variation 09b (Hoag)	Variation 09b (VV)	Revised Base Model	Variation 06b	Variation 08b	Variation 09b
int0702 = hosp_bed_lic_totl*agradm	X	X						X			
int0703 = hosp_bed_lic_totl*rinc	X	X						X			
int0705 = hosp_bed_lic_totl*privcov	X	X						X			
int0706 = hosp_bed_lic_totl*selfpay	X	X						X			
int0707 = hosp_bed_lic_totl*mc	X	X						X			
int0801 = trauma*sched	X	X									
int0803 = trauma*los	X	X						X			
int0804 = trauma*trnsplnt	X	X						X			
int0805 = trauma*numodiag	X	X						X			
int0806 = trauma*numoproc	X	X						X			
int0807 = trauma*neoplsn	X	X						X			
int0808 = trauma*birthdef	X	X						X			
int0809 = trauma*perinatal	X	X						X			
int0810 = trauma*resp	X	X						X			
int0811 = trauma*circ	X	X						X			
int1701 = nicu*sched	X	X									
int1703 = nicu*los	X	X						X			
int1704 = nicu*trnsplnt	X	X						X			
int1705 = nicu*numodiag	X	X						X			
int1706 = nicu*numoproc	X	X						X			
int1707 = nicu*neoplsn	X	X						X			
int1708 = nicu*birthdef	X	X						X			
int1709 = nicu*perinatal	X	X						X			
int1710 = nicu*resp	X	X						X			
int1711 = nicu*circ	X	X						X			
int1801 = teach*neoplsn	X	X						X			
int1802 = teach*resp	X	X						X			
int1803 = teach*circ	X	X						X			
int2001 = thosp*female	X	X						X			
int2002 = thosp*agradm	X	X						X			
int2003 = thosp*rinc	X	X						X			
int2005 = thosp*privcov	X	X						X			
int2006 = thosp*selfpay	X	X						X			
int2007 = thosp*mc	X	X						X			
int2008 = thosp*sched	X	X									
int2010 = thosp*los	X	X						X			
int2011 = thosp*trnsplnt	X	X						X			
int2012 = thosp*numodiag	X	X						X			
int2013 = thosp*numoproc	X	X						X			
int2014 = thosp*neoplsn	X	X						X			
int2015 = thosp*birthdef	X	X						X			

Variable Name/Definition	Base model	Hoag and Victor Valley						Summit/Sutter			
		Revised Base Model	Variation 04b	Variation 06b	Variation 08b	Variation 09b (Hoag)	Variation 09b (VV)	Revised Base Model	Variation 06b	Variation 08b	Variation 09b
int2016 = thosp*perinatal	X	X						X			
int2017 = thosp*resp	X	X						X			
int2018 = thosp*circ	X	X						X			
int2101 = thosp*forprofit	X	X						X			
int2102 = thosp*teach	X	X						X			
int2103 = thosp*ftesperadjacbedrn	X	X						X			
int2104 = thosp*netppeperadjpatday	X	X						X			
int2105 = thosp*transplant	X	X						X			
readmit_30_day			X								
kaiser				X					X		
int3001 = er*thosp					X					X	
int3002 = cancer*thosp					X					X	
int3101 = aha_stemi*female (Hoag)						X					
int3102 = aha_stemi*agyradm (Hoag)						X					
int3103 = aha_stemi*rinc (Hoag)						X					
int3105 = aha_stemi*privcov (Hoag)						X					
int3106 = aha_stemi*selfpay (Hoag)						X					
int3107 = aha_stemi*mc (Hoag)						X					
int3201 = aha_heart_fail*female (Hoag)						X					
int3202 = aha_heart_fail*agyradm (Hoag)						X					
int3203 = aha_heart_fail*rinc (Hoag)						X					
int3205 = aha_heart_fail*privcov (Hoag)						X					
int3206 = aha_heart_fail*selfpay (Hoag)						X					
int3207 = aha_heart_fail*mc (Hoag)						X					
int3301 = cancer_list*female (Hoag)						X					
int3302 = cancer_list*agyradm (Hoag)						X					
int3303 = cancer_list*rinc (Hoag)						X					
int3305 = cancer_list*privcov (Hoag)						X					
int3306 = cancer_list*selfpay (Hoag)						X					
int3307 = cancer_list*mc (Hoag)						X					
int3401 = ortho_list*female (Hoag)						X					
int3402 = ortho_list*agyradm (Hoag)						X					
int3403 = ortho_list*rinc (Hoag)						X					
int3405 = ortho_list*privcov (Hoag)						X					
int3406 = ortho_list*selfpay (Hoag)						X					
int3407 = ortho_list*mc (Hoag)						X					
int3101 = cv_specialty*female (VV)							X				X
int3102 = cv_specialty*agyradm (VV)							X				X
int3103 = cv_specialty*rinc (VV)							X				X
int3105 = cv_specialty*privcov (VV)							X				X
int3106 = cv_specialty*selfpay (VV)							X				X

Variable Name/Definition	Base model	Hoag and Victor Valley						Summit/Sutter			
		Revised Base Model	Variation 04b	Variation 06b	Variation 08b	Variation 09b (Hoag)	Variation 09b (VV)	Revised Base Model	Variation 06b	Variation 08b	Variation 09b
int3107 = cv_specialty*mc (VV)							X				X
int3201 = rehab_specialty*female (VV)							X				X
int3202 = rehab_specialty*agradm (VV)							X				X
int3203 = rehab_specialty*rinc (VV)							X				X
int3205 = rehab_specialty*privcov (VV)							X				X
int3206 = rehab_specialty*selfpay (VV)							X				X
int3207 = rehab_specialty*mc (VV)							X				X
int3301 = resp_specialty*female (VV)							X				X
int3302 = resp_specialty*agradm (VV)							X				X
int3303 = resp_specialty*rinc (VV)							X				X
int3305 = resp_specialty*privcov (VV)							X				X
int3306 = resp_specialty*selfpay (VV)							X				X
int3307 = resp_specialty*mc (VV)							X				X

Base Model and Variations	Description
Diversion 1	Base model
Diversion 2	Indicator for whether the patient had a readmission within 30 days
Diversion 3	Medicare/Medicaid discharges included
Diversion 4	Interaction terms of patient travel time to the hospital with entry to the hospital through the ER and patient travel time to the hospital with a patent primary diagnosis of cancer
Diversion 5	Alternative data on hospital specialties interacted with patient characteristics

APPENDIX C: ACKNOWLEDGMENTS

We would like to thank the following people for agreeing to serve on our review panel for this document. We greatly appreciate their feedback and expertise; however, any shortcomings or errors are the sole responsibility of the authors.

- Deborah Haas-Wilson
- Paul Ginsburg
- John Weigand
- Nathan Wilson
- Kathleen Foote
- Quyen Toland